SENSOR VALIDATION AND FUSION WITH DISTRIBUTED 'SMART DUST' MOTES FOR MONITORING AND ENABLING EFFICIENT ENERGY USE

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Abstract

MEMS (microelectronic mechanical systems) sensors make a rich design space of distributed networked sensors viable. They can be deeply embedded in the physical world and spread throughout our environment like "smart dust". Today, networked sensors called Smart Dust motes can be constructed using commercial components on the scale of a square inch in size and a fraction of a watt in power. High-density distributed networked sensors have recently been targeted for use in research devoted to the efficient use of energy. Such networks require a large number of sensors for control at different levels. However, in reality, sensor information is always corrupted to some degree by noise and degradation, which vary with operating conditions, environmental conditions, and other factors. To overcome these shortcomings, sensor validation is needed to assess the integrity of the sensor information and adjust or correct as appropriate. Sensor fusion of both disparate and redundant (physical and functional) sensors is essential for control and to achieve high sensor data fidelity. In this paper we have isolated a specific domain within the built environment, and present an influence diagram model by which to answer the decisions concerning how to most efficiently condition that space throughout the day. Key issues include the aggregation of heterogeneous information, management of uncertainty at various levels, appropriateness assessment of current validation and fusion algorithms, temporal changes and decision-making strategies.

1. Distributed MEMS Sensors – Smart Dust

The goal of the Smart Dust project is to build a self-contained, millimeter-scale sensing and communication platform for a massively distributed sensor network [16,24]. These devices will ultimately be around the size of a grain of sand and will contain sensors, computational ability, bi-directional wireless communications, and a power supply, while being inexpensive enough to deploy by the hundreds.

There exist endless possibilities for the applications of these devices. The wireless sensing capabilities of Smart Dust, combined with its microscopic size give everything in the physical world the potential to be "smart." As the cost of the devices decreases, and the number of sensors collated into a network increases, the need for sensor fusion and validation techniques becomes increasingly necessary. Similarly, as the real-world applications of these sensor webs become increasingly sophisticated, the integrity of the information conveyed within the web, and the decisions that can be executed merit increasing levels of attention. Before turning to the details of the research questions afforded by Smart Dust applications, we review the basic architecture and design of the macroscale motes available today.

1.1 Architecture and Operation of Smart Dust Motes

While dust-sized sensing and communication units are the goal of the project, macro-scale units called motes have been successfully developed and are in use for a variety of research projects. The motes are based on a common architecture, but each mote has a unique set of communication and sensor capabilities [10,26,30,31]. Smart motes consist of a microcontroller, sensors and a communication unit. The communication unit is one of the following: an RF transceiver, a Laser Module, or a corner cube reflector. The sensors measure a number of physical or chemical stimuli such as temperature, humidity, ambient light, vibration, acceleration, or air pressure.

Periodically the microcontroller receives a reading from one of the sensors, processes the data, and stores it in memory. A receiver is used to receive incoming communications from other motes or from the base station. Sensor data and messages can be transmitted back to the base station or to other motes in the network with the use of the corner cube retroreflector, laser or RF transceiver.

The microcontroller determines the tasks performed by the mote, and controls power distribution to the various components of the system in order to minimize total consumption. Power conservation is achieved largely through the use of timers. When a timer expires, it signals a part of the mote to carry out a task, then powers off. Upon completion of the task, everything is powered down and the timer begins counting again. The microcontroller can receive several types of packets, including new program code that is stored in the program memory. This capability enables remote modification of the mote's behavior. Incoming packets may also contain messages from the base station or other motes. The message may contain specific instructions for the mote, or it may simply be a message that is in transit to some other destination.

Some of the timers mentioned above are dedicated to control of the sensors. When one of these timers expires, it powers up the corresponding sensor, takes a sample, and converts it to a digital word. If data are interesting, the microcontroller can assemble it into a packet for transmission. Alternatively, the sensor data may be stored directly in the mote's SRAM.

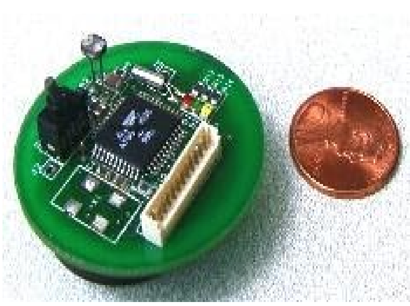

Fig.1: Smart Dust Mote [32].

1.2 Current Applications of Smart Dust Motes

Returning to the idea that with Smart Dust anything has the potential to be made 'smart', we can appreciate the variety of applications for which that these devices have been considered: inventory control and product monitoring, surveillance and security, internal spacecraft monitoring, and weather modeling and monitoring [16].

Smart Dust motes have already been used, or are currently being used in research experiments at U.C. Berkeley to develop motion-tracking webs for vehicle surveillance [30]. Also developed was an acceleration-sensing glove that can be used as a virtual keyboard [31].

Improvements to the efficiency of energy use have also been targeted as one of the major impact areas for distributed MEMS sensors. Research currently being conducted by U.C. Berkeley's Center for the Built Environment [5] and the UC Berkeley Center for Information Technology Research in the Interest of Society (CITRIS) [7,11] are beginning to explore the potential uses for Smart Dust motes in energy applications within buildings. Research based upon the use of Smart Dust motes for energy conservation and efficiency is expanded upon and further explored in the remainder of this paper.

2. The Efficient use of Energy

Energy efficiency has recently come to the forefront of energy debates, especially in the state of California ("energy efficiency" referring to both the total energy required over time, as well as the peak power demand at any given instant of time.) This focus on efficiency has been driven by the deregulation of electrical-energy distribution, the increasing price of electricity, and the implementation of rolling blackouts. It has been determined that a 1% reduction in peak electricity demand can lead to a 10% reduction in wholesale prices, and that a 5% reduction can cut the price in half [4,25].

2.1 Energy Use in the Built Environment

Currently, approximately one third of all primary energy consumption can be attributed to buildings. Of this third, two thirds of the primary energy use is in the form of electricity used for water heating, lighting, HVAC, and operation of electrical machinery. In addition, two thirds of the electrical energy produced in the United States is used in buildings [4,25].

In spite of the significant proportion of energy that is consumed within buildings, the use of this energy is not very efficient. A study conducted by the Interlaboratory Working Group in 2000 championed efforts to reduce energy consumption in buildings, arguing that savings of up to 18% in primary energy use could be gained [4,25]. Although it is widely accepted that energy efficiency improvements are economically and environmentally beneficial, we have not yet as a nation made large strides in this direction with respect to the *built environment*.

A significant obstruction in solving electrical consumption and efficiency problems in buildings has been a lack of information – we currently don't know, to much accuracy, the costs to run individual appliances at various times throughout the day, how much electricity individual appliances consume, or what causes the inefficiencies of individual appliances and systems of energy consuming devices. The Interlaboratory Working Group 2000 has identified gaps in the information loop between supplier and end-user as the critical barrier to technological innovation in these areas [4,25].

2.2 Improving Efficiency with Advanced Information Technologies

One approach toward improving the efficiency of the energy distribution and consumption infrastructure within the built environment involves the development of large-scale integrated information technology systems [25]. For example, the Center for Information Technology Research in the Interest of Society (CITRIS), a research center established under the California Institutes on Science and Innovation (CISI), has made the development of Societal-scale Information Systems (SISs) a prime research agenda [7]. These systems rely on high-density sensing and actuating networks that will allow *existing* environmental control technologies to operate in more sophisticated and energy-efficient ways. High-density sensing and actuating networks systems also have the potential to enable *new* energy-efficient control technologies to become feasible for the first time [25]. In the remainder of this paper we isolate a domain within the built environment, and outline a research program that leverages the sensing, size and communication advantages offered by Smart Dust motes in order to improve the efficiency of energy consumption within that domain. To analyze, simulate and experimentally validate our research, we have developed a three-tiered hierarchical model of the sensor validation, fusion and decisions under consideration.

3. Heating, Ventilating and Lighting of Shared Indoor Space

Indoor space that is shared by multiple persons throughout the day offers a promising domain in which to focus our efficiency improvement efforts. In the discussions that follow we will limit ourselves to shared spaces in which there are multiple sources of artificial light with the capacity to be dimmed, as well as windows that receive varying levels of light during the day. Let us further assume that the shared space under consideration has both space heating and ventilation and multiple sources of local radiant heat and fans. In this paper, we will focus on the lighting scenario as it can be implemented with readily available building technologies. The heating and ventilating example is more complex and will require significant changes in the built environment [3]. However, the lighting model can be extended to heating and ventilating in order to analyze the cost/benefit trade-offs for these design changes.

3.1 Modeling the Lighting Problem as a Hierarchical Influence Diagram

With a focus on improved energy efficiency with lighting, we are concerned with how Smart Dust motes can be used in parallel with outside ambient and artificial light sources to most efficiently light the space throughout the day with varying use patterns? We develop an influence diagram model [29] (Bayes' nets [21,22] with the addition of decision or control nodes) to model the uncertain influences and information available to the system control. Each sensor in the net provides data on ambient temperature and light conditions, as well as patterns of human occupancy. The sensors throughout the room can be grouped into regional clusters based upon their proximity to the artificial sources of light and heat/ventilation throughout the space. These regions of the room that correspond to the locations of the clustered sensors interact, resulting in the global light and heat /cooling conditions associated with the entire space.

Our influence diagram model of the environmental conditions, sensors, and points of control in the room is a three-tiered hierarchical arrangement of the information necessary to perform sensor validation, sensor fusion and decision-making at various levels – local, regional, and global [18,35]. For example, from a local perspective, the model must be able to distinguish between individual sensors, and evaluate the integrity of the data from each. Thus sensor validation can occur at the individual sensor level. From a regional perspective, the model must be able to incorporate the data from multiple, many of them redundant, sources in order to determine spatially

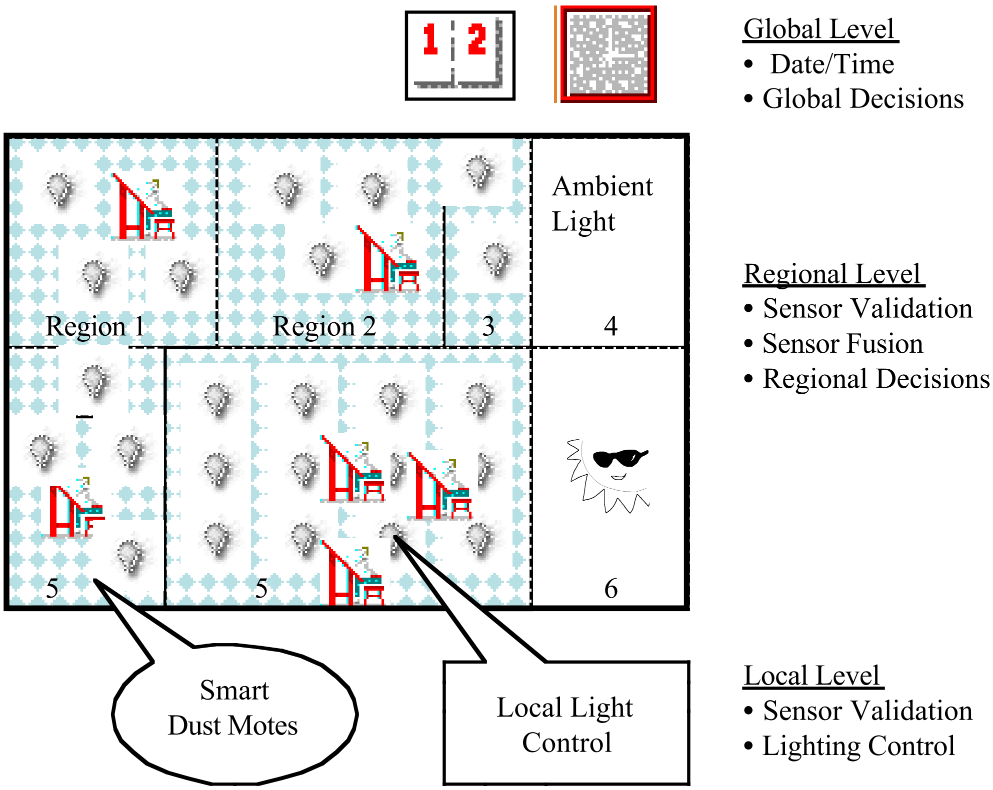

Fig. 2: Hierarchical Levels of the Influence Diagram: Local, Regional and Global.

distributed patterns as well as average conditions for a given actuating zone within the environmental control system; thus sensor validation and fusion can be performed at the regional level [6,9,10] as well as some control of regional light sources. From a global perspective, the model must be able to determine how to control global light sources, in order to maximize the efficiency of energy consumption. Other over-riding global decisions might include emergency lighting or preparation for voluntary black outs.

A brief summary of the influence diagram nodes and influences we use in our model follows. An influence diagram is an acyclic directed network with nodes representing variables critical to the problem and the arcs representing their interrelationships. The general influence diagram model consists of five kinds of nodes: state, sensor, deterministic, decision/control and value nodes.

State Nodes : Any state in the system can be represented by a state node, graphically shown as a circle or ellipse. In our model, the state nodes are the features of the state of light intensity in a region of the room (e.g., spatial distribution and average light), the occupancy in the room (Boolean or spatial distribution), along with the states of the sensors. Specialized forms of state nodes are sensor and deterministic nodes.

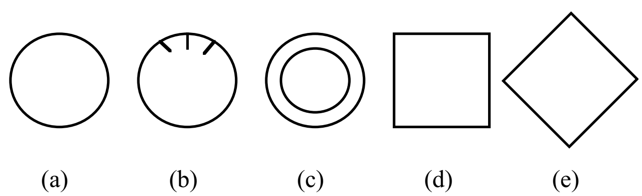

Fig. 3: Nodes (a) state, (b) sensor, (c) deterministic, (d) decision/control and (e) value.

Sensor Nodes : A sensor node represents a measurement sensor that could be directly 'read' by an operator or controlling system. It might also represent a physical state of the system that is immediately obvious to the operator by means of human sensory capabilities, such as sight, hearing or smell. All of our Smart Dust motes are modeled using the sensor icon (Fig. 3b) in our model. In our lighting model, we have segmented the influence diagram into room regions using an "i" sub/super-script. We consider a system with the set of N^i non-sensor state variables representing the features of light intensity in each region i, denoted by $\mathbf{X_i} = \{x_{i1}, x_{i2} \ldots x_{iN^i}\}$. and a set of M^i *sensors* or *observables* $\mathbf{S_i} = \{S_{i1}, S_{i2} \ldots S_{iM^i}\}$ for each region i. We assume that we sense the occupancy within the regions through a set of specialized Boolean *trigger* sensors $\mathbf{T} = \{t_1, t_2, \ldots t_k\}$, such as motion sensors. A high density network of motion sensors could also be used to determine the spatial distribution of occupancy as well.

Deterministic Nodes: A deterministic node is one in that performs a deterministic or algorithmic operation on information fed into it. The output of a deterministic node need not be deterministic if the inputs are probabilistic or fuzzy. In our model, the sensor validation and fusion algorithms are modeled as deterministic nodes. Sensor validation occurs at the local and regional levels, but sensor fusion occurs only at regional and global level.

Decision/Control Nodes: A decision or control node represents decision options in an influence diagram. Arcs going into a decision node represent information available to the decision maker or controller at the time the decision is to be made. In our model, the decisions are to turn on/off lights or increase/decrease the lighting to a continuous value of intensity. Although control options are available at all three hierarchical levels, the decisions are made in consideration of the value at the regional and global levels only. For example, even though it is possible to control each light source independently, our lighting model makes decisions based on those sensor readings and values first at the regional level and then at the global level.

Value Node: The value node represents the value or cost function associated with the problem being model. In our case, the value function should drive the decisions to improved efficiency and could be represented as a cost function minimizing the predicted cost of energy in dollars over the time period being considered. The value node only operates at the regional and global levels. Micro-decisions at the component level are not considered.

The interpretation of the relationships represented by the arcs in an influence diagram depends on the type of the nodes they connect. Arcs going into state nodes represent *conditional influences* as shown in Fig. 4 a,b&d. Formal calculi have been developed for both probabilistic relationships (using Bayesian [22] or fuzzy probabilities [15]) and fuzzy functions [13].

Arcs between state nodes can be reversed through legal transformations on the diagram, providing a cycle is not introduced, using Bayes' rule for probabilistic models [29] and abduction rules for fuzzy influence diagrams [13]. Arcs to and from decision nodes serve a different function and can not be reversed without changing the basic structure of the decision model. An influence arc from a decision node to a state node (Fig. 4d) indicates causality in the sense that each decision option restricts the event space of the state variable. Arcs going into decision nodes are *informational* and show which variables will be known at the time a decision is made (Figs. 4c). *No-forgetting* arcs are placed between decision nodes to signify that decisions are sequential in time and the value of past decisions is remembered (Fig. 4e). Arcs into the single value node signify which nodes directly influence the goal (Fig. 4f). Again, a probabilistic influence diagram without decision nodes is equivalent to a Bayes' belief network [29].

The lack of an arc is a stronger statement of the modeler's knowledge of the system than the existence of an arc. The presence of an arc indicates that a *possible* dependency exists, while the lack of an arc states strongly that *no dependency* exists. A variable is said to *influence* a state node *y* if information about *x* gives new information about *y,* given any other conditioning information.

3.2 Regional Validation, Fusion and Decision Model

The diagram in Fig. 5 illustrates our proposed hierarchical layout of sensors within the room being conditioned for the lighting problem. The reasoning that led to the inclusion or omission of dependencies within the diagram is as follows. Clearly, the actual presence of humans in the room should influence what the motion detector reads – thus the arc from the "people?" state node to the motion detector sensor. Similarly, true light intensity influences what the light sensor reads. As most of the regions are not separated by walls, the true light intensity in one region will be influenced by the true light intensity in neighboring regions – thus the arc from the light state node in region 1

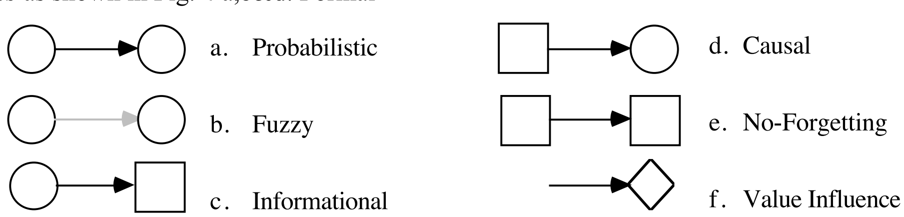

Fig. 4: Six Roles for Arcs in an Influence Diagram.

to the corresponding node in region 2. The actual presence of humans in the room would influences the actual state of the lighting if the human has direct control over the lighting in the time period under evaluation – thus the arc from "people?" to "light" in each region. For a first order approximation, we have not included the influence of human occupancy in region 1 on actual lighting in region 2. The influence of actual human presence on the reading of the light sensor, conditioned on the true intensity of the light (i.e., given the arc from the true light state to the light sensor), has also been determined to be secondary, and has been omitted in this version.

The date and time of day is information that is considered to be universally available to all sensing motes. It is a straightforward conclusion that the time of day influences the true state of human presence in each region, as well as the true state of light intensity in the region. The date and time of day also influences the cost of electricity and assumed to be known at the time of any regional or global decision.

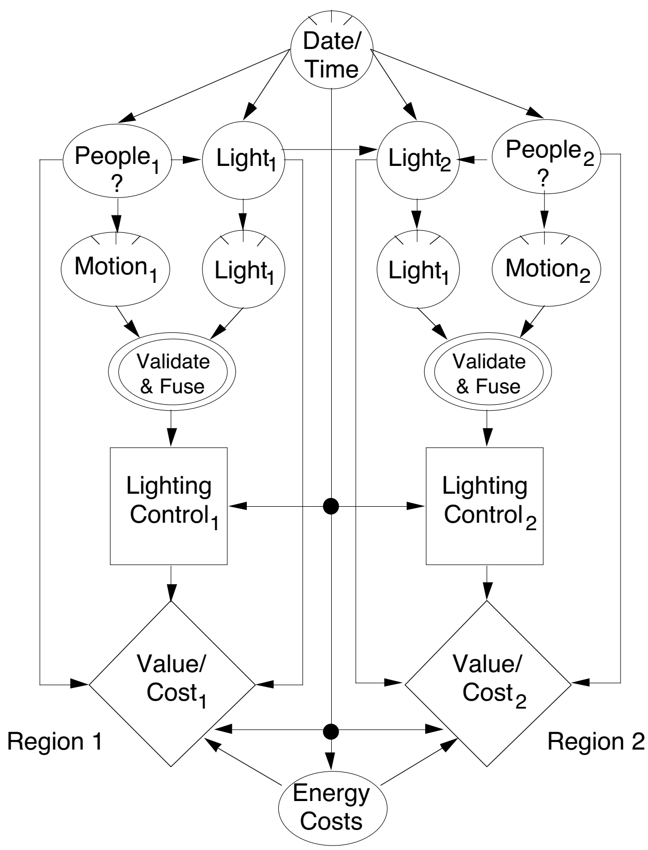

Fig. 5: Influence Diagrams of Two Contiguous Regions for the Lighting Problem.

3.3 The Decision Problem

The decision problem at hand is how to most *efficiently* light, ventilate and heat the space under consideration. One aspect of efficiency, that of limiting total electrical demand, is met through the intelligent real-time determination of how best to combine the artificial resources with one another, or with sunlight. However, another aspect of efficiency is that of limiting the total cost of conditioning the space in question. Limiting peak demand is further related to the cost of conditioning the space in that it is critical to reducing the wholesale prices of electricity [4].

Decisions arrived at within the model depend on the value function. The value function attempts to minimize overall average energy consumption and peak energy consumption, and to maximize human satisfaction. The cost of electricity is included in the model as a dynamic variable in order to incorporate the elevated cost of electricity during periods of peak demand. The Center for the Built Environment [3,5], has developed an "occupant satisfaction survey" and metrics for "benchmarking building quality" and has conducted numerous studies on both objective measures and human subjective perceptions of indoor environmental quality. As we learn more from experts from this center, the human satisfaction parameters may be further developed and separated out from the value function into their own state nodes.

4. Future Research

This paper describes work in progress aimed at developing an influence diagram model that identifies the key features, influences and decision options associated with sensor validation and sensor fusion of Smart Dust motes for enabling efficient energy use, starting with the lighting problem. Refinement of the influence diagram used to model the problem is part of the research that we have planned for the immediate future. Within this framework we are evaluating research in sensor monitoring, validation, fusion, and fault detection along with current work in computer-aided MEMS design [8,36] to evaluate a range of fuzzy [e.g., 14], probabilistic [e.g., 2,6,17,28,34] or hybrid [e.g., 12,23] algorithms for appropriateness to this problem. One key issue in this evaluation will be the ability to mange the temporal aspects of the problem. Our influence diagram model can be made dynamic by updating and linking influences over periodic time segments [1,27]. Which states should be monitored on a periodic basis? Which sensors and decisions should only be considered after a trigger event or threshold is reached? What are appropriate response times that balance energy efficiency and human factors? What is the optimal density of Smart Dust motes and what algorithms meet the associated scalability needs? [9,16,18,19,20].

Based on our evaluation of suitability, the most promising algorithms will be tested on data from a network of Smart Dust motes currently being used to monitor occupancy, temperature and ambient conditions in Cory Hall at UC Berkeley [25]. Using these data, we will also characterize sensor noise and failure models for the temperature and light sensors used in Smart Dust motes [33]. These characterizations will then be incorporated into a group of proposed methods for integrating monitoring, validation, fusion and diagnosis techniques into Smart Dust mote infrastructures.

Long-term research efforts will be aimed toward developing the methodology presented within this paper for application to the other types of sensors used in Smart Dust motes. The methodology can be assessed for efficacy, and altered for improvement, with the end goal of extending and re-applying it to the design of future generations of Smart Dust motes and their energy-related applications.

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